# A Fuzzy System for Fault Diagnostics in Power Electronics Based Brake-by-Wire System

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Abstract - This paper presents a structured fuzzy system for fault diagnostics in a brake-by-wire system. Our focus is on the power electronics switches within a electrical motor. We have developed a simulated model of brake-by-wire system to generate current and voltage signals under the normal condition and six faulty conditions in the power electronics circuit. Our experiments show that the proposed fuzzy diagnostic system is effective in accurately predicting faults as well as the location of faults.

### I. INTRODUCTION

Recently the automotive industry is focusing attention towards the replacement of more and more mechanical systems in vehicles using either fully electric or a partially electric systems. In addition to the main propulsion, work has progressed towards the replacement of various auxiliary devices, which are currently run by mechanical means, e.g. hydraulic or pneumatic. These devices include steering, brakes, and various mechanical pumps. In general the mechanical systems are relatively heavy, and their packaging is more difficult. Electrical devices use motors, sometimes solenoids, as actuators, and if the motor system fails, the entire electrical system related to the motor ceases to function properly. A motor system consists of several items – battery, wiring, power electronics based switches used to control the motor, an embedded controller with the necessary algorithms, and finally the motor itself. In this paper we present our research in fuzzy diagnostics of brake-by-wire systems. Our focus is on the power electronics switches since they are often considered to be the weakest link in the system. The objective of fault diagnostic in the power electronics of the brake-bywire system is to accurately locate any faults within the circuit as soon as they occur.

Fault diagnostics for internal combustion (IC) engine vehicles has been well investigated [1-5], but not so for electric or hybrid vehicles. However, Research in electrical system diagnostics is getting to be active. Moseler and Isermann [6] described a black box type of model using a polynomial differential-algebraic equation with application to a brushless dc machine. The estimated system parameters under normal and faulted conditions are compared with the current system parameter values, and if any discrepancy with the normal condition shows, then a faulty condition is declared. However, the parameter-estimated model of this kind can easily lose the intuitive focus of the system, and in

general cannot point towards the specific problem and its location. In addition, sometimes the model can encounter a topological change after a fault, and hence the premises based on which the model was originally developed and the parameters estimated, may not hold anymore. Jacobina and Silva [7] presented an approach that uses the direct comparison of voltages measured at certain key points of an electric drive system with an open loop control. Fenton, McGinnity, and Maguire [5, 8] gave an overview on the fault diagnostics of electronic systems that used intelligent techniques such as rule-based systems, case based reasoning, fuzzy logic and artificial neural networks (ANN). In this paper we explore an effective fuzzy system for fault diagnostics. Fuzzy systems have been used successful in many applications including control theory where gradual adjustments are necessary, control systems, business and even the stock exchanges [9-17]. The nature of fuzzy rules and the relationship between fuzzy sets of differing shapes provides a powerful capability for incrementally modeling a system whose complexity makes traditional expert systems, mathematical models, and statistical approaches very difficult. The most challenging problem in signal diagnostic problem is that knowledge of most signal faults is incomplete and vague due to the complexity of modern vehicles. This uncertainty leads us to seek a solution using fuzzy diagnostic methods. This paper presents a structured hierarchical fuzzy diagnostic system designed for the detection of multi-class faults in a Brake-By-Wire circuit system.

## II. A BRAKE-BY-WIRE SYSTEM

Figure 1 illustrates the system architecture of a fully electro-mechanical brake-by-wire system currently under study. In this system, the battery is connected to the actuator motors and power electronics through wirings. The motor selected for our study is a regular brushed dc motor, which is inexpensive and is available in the automotive industry abundantly, which can be permanent magnet based or have a field winding. The system has 4 actuator motors corresponding to each wheel and located in the vicinity of the brakes. The thick lines in Figure 1 represent the power lines from the battery. The signal lines are shown in thin lines. The position signal from the brake pedal goes to a controller, which generates control signals to activate each of the motors. Although a single thin line is shown running from the

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Form Approved OMB No. 0704-0188 controller to the power electronic blocks, in reality they will be separate. This can help all the 4 actuators to run independently, and is more robust during a failure of any one or more of the actuators and can lead to better graceful degradation during a failure mode.

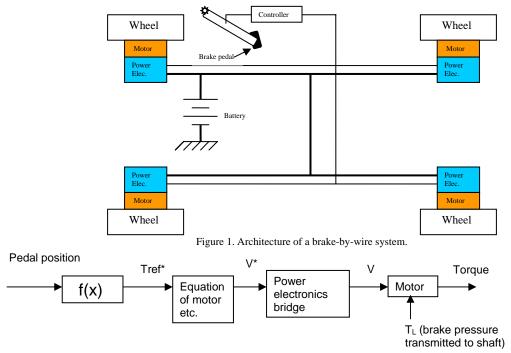


Figure 2. The system diagram for the brake-by-wire system

Figure 2 illustrates the system block diagram of a simulation model implemented by the authors using Matlab Simulink. The electromechanical system equations used in the simulation are as follows. Note we assume a brushed dc motor used in the brake-by-wire system:

Motor input voltage = 
$$V = R_a I_a + L_a di_a/dt + K\omega$$
 (1)

Torque = 
$$T = K i_a$$
 (2)

$$T = J d\omega / dt + B \omega + T_L$$
 (3)

The reference voltage V\* can be derived if Tref\* is given:

$$V^* = R_a (Tref^*/K) + (L_a/K) (d(Tref^*)/dt)$$
 (4)

In the above equations  $R_a = \text{motor}$  armature resistance,  $L_a = \text{motor}$  inductance, K = speed constant = torque constant (assuming consistent units are used),  $i_a = \text{motor}$  current,  $\omega = \text{motor}$  speed in rad/sec, J = moment of inertia, B = frictional coefficient,  $T_L = \text{load}$  torque on the motor shaft,  $V^* = \text{reference}$  voltage desired at the motor terminal to generate the desired torque at the motor shaft, and  $\text{Tref}^* = \text{reference}$  torque desired at the motor shaft to create the necessary braking effort. Tref\* can be determined by the brake pedal force.

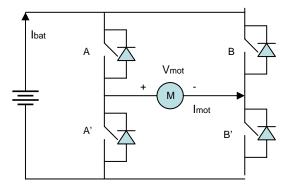
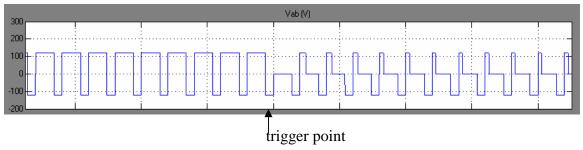


Figure 3. The inverter circuit diagram for the brake-by-wire system

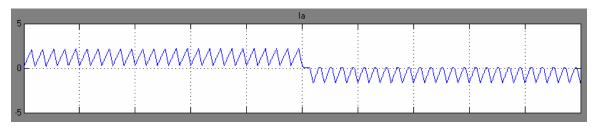
The power electronics circuit to actuate the motor is presented in Figure 3. Based on the equation (4), a reference voltage is obtained, which is fed to the motor terminals. This voltage is obtained from the dc battery by a mean of PWM (pulse width modulation) techniques which allows synthesizing the desired  $V^*$  based on the pulsed voltage initiated by the switches. This

system model shown in Figure 1 through 3 is implemented in BBW-SIM, a simulated model generated using Matlab-Simulink based on the equations (1) through (4). Figure 4

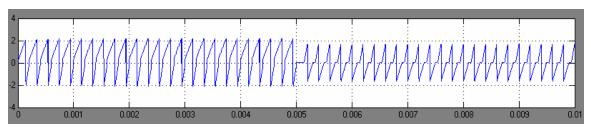
shows the current and voltage signals generated by BBW-Sim before and after switch A is broken.



(a) Vmot before and after gate A broken, duty cycle = 70% (in 0.004s)



(b) Imot (simulation) before and after gate A broken



(c) I<sub>bat</sub> signal before and after gate A broken

Figure 4. Voltage and Current signals of motor before and after gate A broken

# III. A FUZZY DIAGNOSTIC SYSTEM FOR FAULT DETECTION IN A BRAKE-BY-WIRE SYSTEM

Based on the brake-by-wire system presented in the last section, we define six faulty classes:

- Switch A is broken
- Switch B is broken
- Switch A' is broken
- Switch B' is broken
- Both switches A and A' are broken
- Both switches B and B' are broken

We have developed a structured fuzzy diagnostic system shown in Figure 5. Three signals are used in the fault diagnostics,  $I_{\text{bat}}$  is the current of battery,  $I_{\text{mot}}$  is the current of motor, and  $V_{\text{mot}}$  is the voltage of motor. The signals are acquired simultaneously. The signals are analyzed at a segment-by-segment basis. Fault detection is performed on a segment-by-segment basis. All input signals are segmented using the same fixed sized segments and the two adjacent

segments are overlapped in 1/3 of each segment in order to maintain continuity of information flow between segments. Each segment is represented by three features, Min, Max, and Average. Every detection system  $F_i$ , for  $i=1,\,2,\,...,\,6$ , is a fuzzy system modeled as follows. Fuzzy reasoning is performed within the context of a fuzzy system model, which consists of control, solution variables, fuzzy sets, proposition (rule) statements, and the underlying control mechanisms that tie all these together into a cohesive reasoning environment. In this application a fuzzy system  $F_i$  has nine fuzzy control variables,

X={ $I_{mot}^{\min}$ ,  $I_{mot}^{\max}$ ,  $I_{mot}^{ave}$ ,  $I_{bat}^{\min}$ ,  $I_{bat}^{\max}$ ,  $I_{bat}^{ave}$ ,  $V_{mot}^{\min}$ ,  $V_{mot}^{\max}$ ,  $V_{mot}^{ave}$ }, and one solution variable,  $y_i$ , which models the output of each system. The fuzzy learning algorithm presented in [1] is used to generate fuzzy knowledge base for each fuzzy system based on the data generated by the simulation model presented in the last section.

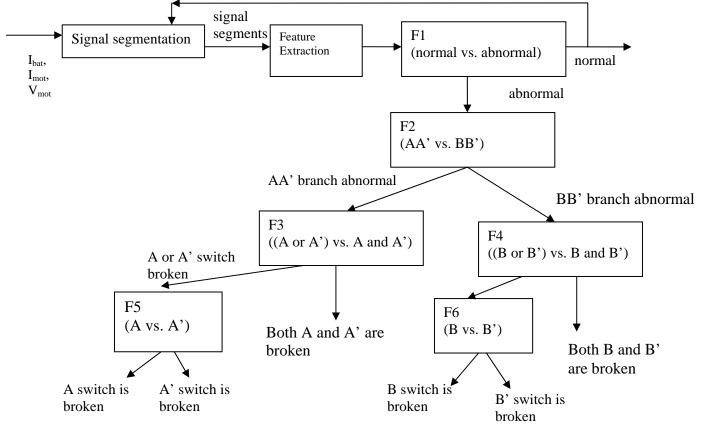


Figure 5: A structured fuzzy system for fault diagnostics in a brake-by-wire system.

We use the simulation model, BBW-SIM, described in the last section to generate training and testing data. The BBW-SIM has the following simulation parameters, DC motor with  $V_{DC} = 100V$ , Ra = 8.98 ohm, La = 0.00535 H, Initial speed =  $650/60^*2^*$ pi rad/s, Friction Torque = 0.1 Nm. The inverter's parameters were set to PWM Frequency = 5k Hz. Three signals,  $I_{bat}$  the current of battery,  $I_{mot}$  the current of motor, and  $V_{mot}$  the voltage of motor, are measured for all six faulty classes presented above. Each faulty event was triggered at

the end of first second and the entire simulation takes 2 seconds.

For the signal data generated by each of the six faulty classes, we first segment all three signals  $I_{mot}$ ,  $I_{bat}$  and  $V_{mot}$ , simultaneously into segments of 16 samples in width with an overlap of 5 samples between two adjacent segments. We randomly divided the signal segments into training and test sets with an equal number of faulty segments from all the faulty classes plus the normal class, which results in 966 segments in each set.

Table 1. Performances of individual fuzzy systems in the structured hierarchical diagnostic system.

Fuzzy systems	Class 1Correct	Class 2 Correct	Overall Reject
	Rate (%)	Rate (%)	Rate (%)
F1 (normal vs.	100%	100	0
abnormal)			
F2 (AA' branch	100%	100	0
vs. BB' branch)			
F3 (A or A' vs	100%	100	0
A and A')			
F4 (B or B' vs B	100%	100	0
and B')			
F5 (A vs A')	58.7%	100%	20.7%
F6 (B vs B')	100%	100	0

Table 2. Performance of the structured hierarchical diagnostic system for Brake-by-Wire				
Faulty classes	Correct Rate			
normal	100			
A broke	58.7			
A' broke	100			
A and A' broke	100			
B broke	100			
B' broke	100			
B and B' broke	100			
Overall performance	94.1			

Table 3. Performance of the fuzzy diagnostic system modeled with normal against each faulty class				
Faulty classes	Correct Rate			
normal	100			
A	0			
A'	0			
AA'	10.87			
В	80.43			
B'	100			
BB'	91.30			
overall	54.66			

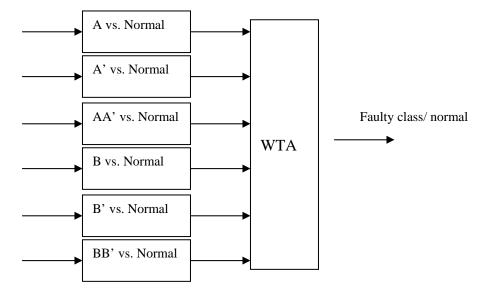


Figure 6. A fuzzy diagnostic system modeled fault-against-normal scheme.

The performances of the individual fuzzy systems in the proposed structured hierarchical fuzzy system on the test data are shown in Table 1 and Table 2. Table 1 shows the performances of each of the six fuzzy systems and Table 2 shows the overall system performance on all six faulty classes and the normal condition.

For the purpose of evaluating the structured hierarchical fuzzy diagnostic system, we implemented a different fuzzy diagnostic system modeled with an fault-against-normal scheme. Figure 6 illustrates the architecture of this system. Six fuzzy systems are developed; each was trained by one faulty class against the normal class. The decision module, WTA(Winner-Take-All), selects the output class that has the highest fuzzy belief value. The performance of this fuzzy system on the same test set is shown in Table 3. It is clear that the structure hierarchical diagnostic system gave a much better performance over all classes.

## IV. CONCLUSION

We have presented a structured fuzzy system design for fault diagnosis in a brake-by-wire system. The system contains a hierarchy of six fuzzy systems designed structurally meaningful to the Brake-By-Wire circuit system. The experiment results show that this structured hierarchical diagnostic system gives better performance than the fuzzy system modeled using normal against each faulty class.

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#### REFERENCE

 J. Gertler, M. Costin, X. Fang, Z. Kowalczuk, M. Kunwer, R. Monajemy, "Model Based Diagnosis for Automotive Engines-

- Algorithm Development and Testing on a production Vehicle", IEEE Trans on Control Systems Technology, Vol. 3, No. 1, 1995
- [2] M. Nyberg, "Model-based Diagnosis of an Automotive Engine Using Several Types of Fault Models", IEEE Transaction on Control Systems Technology, Vol. 10, No. 5, pp 679—689. 2002.
- [3] Yi Lu Murphey, Hong Guo, Jacob A. Crossman, and Mark Coleman, "Automotive Signal Diagnostics Using Wavelets and Machine Learning," IEEE Transaction on Vehicular, November, 2000.
- [4] Jacob A. Crossman, Hong Guo, Yi Lu Murphey, and John Cardillo, "Automotive Signal Fault Diagnostics: Part I: signal fault analysis, feature extraction, and quasi optimal signal selection," IEEE Transaction on Vehicular, July 2003
- [5] Yi Lu Murphey, Jacob A. Crossman, ZhiHang Chen, and John Cardillo, "Automotive Fault Diagnosis Part II A Distributed Agent Diagnostic System," IEEE Transaction on Vehicular, July 2003.
- [6] O. Moseler, R. Isermann, "Application of Model-Based Fault Detection to a Brushless DC Motor", IEEE Trans on Industrial Electronics, Vol. 47, No. 5, pp 1015-1020, 2000.
- [7] R. Ribeiro, C. B. Jacobina, E. Silva, "Fault Detection of Open-Switch Damage in Voltage-Fed PWM Motor Drive System", IEEE Trans on Power Electronics, Vol. 18, No. 2, March 2003, pp 587-593.
- [8] W. Fenton, T. McGinnity, and L. Maguire, "Fault diagnosis of electronic systems using intelligent techniques: a review", IEEE Trans. on Systems, Man, and Cybernetics – Pt. C, Vol. 31, No. 3, Aug 2000, pp. 269-281.
- [9] M. Ayoubi, "Neuro-fuzzy structure for rule generation and application in the fault diagnosis of technical processes," in Proceedings of the 1995 American Control Conference, Seattle, (USA), pp. 2757-2761, 1995.

- [10] C. K. P. Chu and J. M. Mendel, "First Break Refraction Event Picking Using Fuzzy Logic Systems," IEEE Transactions on Fuzzy Systems, Vol. 2, pp. 255-266, Nov. 1994.
- [11] P. Eklund, J. Forsström, A. Holm, M. Nyström and G. Selén, "Rule generation as an alternative to knowledge acquisition: a systems architecture for medical informatics", Fuzzy Sets and Systems, vol.66, pp195-205, 1994.
- [12] H. Kang, "An automated rule design of fuzzy logic controllers for uncertain dynamic systems", 2nd IEEE Int. Conference on Fuzzy Systems, pp261-266, 1993.
- [13] Yi Lu and Tie Qi Chen, "A Fuzzy Diagnosite Model And Its Application In Automotive Engineering Diagnosis," J. of Applied Intelligence, Vol. 9, pp. 231-243, 1998
- [14] H. Nomura, H. Ichihashi, T. Watanabe, "A Self-Tuning Method of Fuzzy Reasoning Control by Descent Method," Procedures of 4th IFSA Congress, Brussels, Vol. Eng. pp. 155-158, 1991.
- [15] Alanna Quail and Adnan Shaout, "State-of-the-Art in Household Appliances using Fuzzy Logic," Second International Workshop on Industrial Applications of Fuzzy Control and Intelligent Systems, College Station, TX, December, 1992.
- [16] F. C.-H. Rhee and R. Krishnapuram, "Fuzzy rule generation methods for high-level computer vision," Fuzzy Sets and Systems, vol. 60, pp. 245-258, 1993.
- [17] T. Takagi and M. Sugeno, "Fuzzy Identification of Systems and its Applications to Modeling and Control," IEEE Trans. Systems, Man, and Cybernetics, vol. SMC-15, No.1, pp. 116-132, 1985.
- [18] Yi Lu, Tie Qi Chen, and Brennan Hamilton, "A Fuzzy System for Automotive Fault Diagnosis: -- Fast Rule Generation and Self-Tuning," IEEE Transaction on Vehicular, Vol. 49, No. 1, January 2000.